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Using High Resolution Satellite Imagery to Map Black Mangrove on the Texas Gulf Coast

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ABSTRACT

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QuickBird false color satellite imagery was evaluated for distinguishing black mangrove [*Avicennia germinans* (L.) L.] populations on the south Texas Gulf Coast. The imagery had three bands (green, red, and near-infrared) and contained 11-bit data. Two subsets of the satellite image were extracted and used as test sites. Supervised and unsupervised image analysis techniques were used to classify the imagery. For the supervised classification of site 1, black mangrove had a producer's accuracy of 82.1% and a user's accuracy of 95.8%, whereas for the unsupervised classification, black mangrove had a producer's accuracy of 100% and a user's accuracy of 60.9%. In the supervised classification of site 2, black mangrove had a producer's accuracy of 91.7% and a user's accuracy of 100%, whereas in the unsupervised classification, black mangrove had a producer's accuracy of 100% and a user's accuracy of 85.7%. These results indicate that QuickBird imagery combined with image analysis techniques can be used successfully to distinguish and map black mangrove along the south Texas Gulf Coast.

ADDITIONAL INDEX WORDS: *Remote sensing, QuickBird satellite imagery, computer image analysis, accuracy assessment, Texas Gulf Coast,* Avicennia germinans.

INTRODUCTION

Mangroves are woody plants that are widely distributed in estuaries and intertidal zones in the tropics and subtropics (Field *et al.,* 1998; Sherrod and McMillan, 1985). There are many benefits to mangrove communities that include serving as breeding grounds to many fish, shellfish, birds, and other wildlife; their physical stability helps to prevent shoreline erosion, providing protection to inland areas during hurricanes and tidal waves (Badola and Hussain, 2005; Ewel, Ong, and Twilley, 1998; Quarto, 2005; Stutzenbaker, 1999).

Several studies have demonstrated the value of remote sensing techniques to document the distribution and extent of mangrove communities. Color-infrared aerial photography and airborne video and digital imagery have been used extensively to distinguish black mangrove populations along the Texas Gulf Coast (Everitt and Judd, 1989; Everitt *et al.,* 1999, 2007; Sherrod and McMillan, 1981). True color digital photography has also been used to map mangroves (Chauvaud, Bouchon, and Maniere, 1998).

Hyperspectral remote sensing that provides tens to hundreds of spectral bands has been used to differentiate mangrove communities. Green *et al.* (1998) employed compact airborne spectrographic images (CASI) hyperspectral data for separating mangroves. Jensen *et al.* (2007) and Yang *et al.* (2008) used AISA + hyperspectral data to discriminate black mangrove communities.

Traditional satellite imagery including Landsat and SPOT data has been used for mapping mangroves and assessing their overall conditions on a regional basis (Gong and Agatsiva, 1992; Jensen *et al.,* 1991; Ramsey and Jensen, 1996). More recently, high spatial resolution satellite imagery from the IKONOS and QuickBird satellites has opened new opportunities for mangrove mapping. Wang *et al.* (2004) used IKONOS and QuickBird imagery in conjunction with different image analysis techniques for distinguishing three mangrove species, including black mangrove, red mangrove (*Rhizophora mangle* L.), and white mangrove [*Laguncularia racemosa* (L.) Gaertn. F.] on the Caribbean coast of Panama.

The objective of this study was to determine the potential of using QuickBird satellite imagery in conjunction with image analysis techniques for distinguishing and mapping black mangrove along the south Texas Gulf Coast.

MATERIALS AND METHODS

This study was conducted along the extreme southern portion of the lower Texas Gulf Coast. This location was selected as a study area because it has several populations of black mangrove. Two different black mangrove populations served as study sites (designated as sites 1 and 2). Site 1 was located on the southwestern portion of South Padre Island. Site 2

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was located at South Bay. The two sites are approximately 2 km apart.

A multispectral satellite image of the study area was obtained on November 24, 2006, from the DigitalGlobe, Inc. (Longmont, Colorado), QuickBird high spatial resolution (2.4 m) satellite.

The QuickBird satellite sensors consist of the blue (450 to 520 nm), green (520 to 600 nm), red (630 to 690 nm) and near-infrared (760 to 900 nm) bands. Prior to delivery, the imagery was radiometrically and geometrically corrected, and rectified to the world geodetic survey 1984 (WGS 84) datum and the Universal Transverse Mercator (UTM) zone 14 coordinate system. The prerectified standard imagery had an average absolute positional error of 23 m and a root-mean-square (RMS) error of 14 m. To improve the positional accuracy, we further rectified the prerectified imagery based on a set of ground points collected from the imaging area with a submeter-accuracy global positioning system (GPS) receiver. The RMS error of the rerectified imagery was reduced to less than 5 m. The procedures for image rectification were performed using Erdas Imagine (Erdas, 2002).

For this study we only used the green, red, and near-infrared bands of the satellite that provided a false color image similar to color–infrared film. Previous research has demonstrated that color–infrared composite imagery is optimum for distinguishing black mangrove (Everitt and Judd, 1989; Everitt *et al.,* 2007). Two subset images were extracted from the satellite scene of the area and used as two study sites (sites 1 and 2). The subset images of the two sites were subjected to both unsupervised and supervised image analysis techniques. The unsupervised technique was an iterative self-organizing data analysis (ISODATA) that performs unsupervised classifications on the basis of specified iterations and recalculates statistics for each iteration. The ISODATA technique uses minimal spectral distance to assign a cluster for each selected pixel. It begins with arbitrary cluster means, and each time the clustering repeats, the means of the classes are shifted. The new cluster means were used for the following iteration.

Initially, the unsupervised classification of the two study sites created 75 classes, which were eventually merged resulting in 5 classes. Each completed classification of site 1 created five classes consisting of black mangrove, wet soil and seagrass, mixed vegetation, soil or roads, and water. For site 2, each completed classification created five classes consisting of black mangrove, soil, mixed vegetation, seagrass, and water. Mixed vegetation consisted of grasses, sedges, and broad-leaved herbs. A few woody plants were included in this class at site 1. These included sabal palm (*Sabal mexicana* K. von Martius), natal plum [*Carissa macrocarpa* (C. Ecklon) A. P. de Candolle], and sea grape [*Coccoloba uvifera* (L.) L.]. The dominant seagrass species included shoalgrass [*Halodule beaudettei* (C. den Hartog) C. den Hartog.], turtle grass (*Thalassia testudinum* J. Banks and D. Solander *ex* K. Koenig), and manatee grass [*Cymodocea filiforme* (F. Kutzing) D. Correll].

For the supervised classification technique, we selected five subsamples from each site of the five surface types from sites 1 and 2 to be used as training sites. The maximum likelihood classifier was then used to classify the two images of the study sites. The classifier uses the signatures from each of the five classes extracted from the training sites (Erdas, 2002).

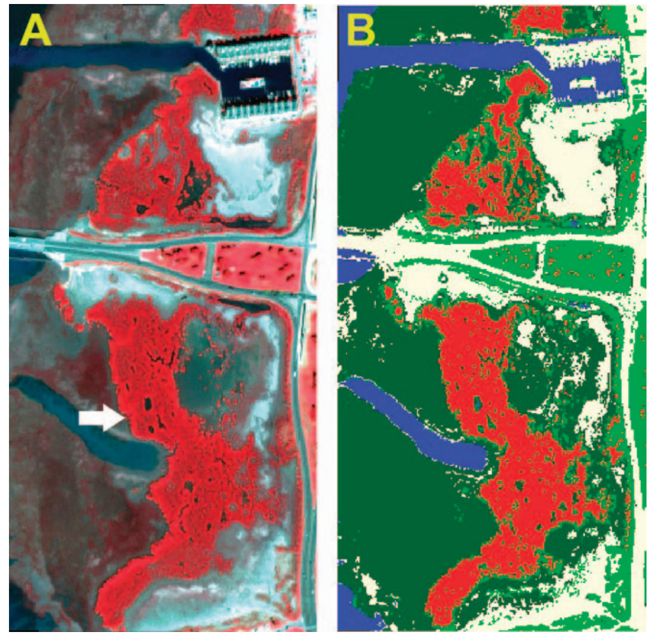

Figure 1. (A) QuickBird false color satellite image obtained November 24, 2006, of site 1 on South Padre Island, Texas. The arrow on print A points to black mangrove. Also shown is (B) the supervised computer classification of the satellite image. Color codes for the various land-use types are: red = black mangrove, light green = mixed vegetation, dark green = wet soil or seagrass, white = soil or roads, and blue = water.

To assess accuracy for the two study sites, 150 points were assigned to the classes in a stratified random pattern using Erdas Imagine software (Erdas, 2002). The number of points assigned to each site was based on the number of classes identified on the site. The geographic coordinates of the points were determined and a GPS receiver was used to navigate to the points for ground truthing. Overall accuracy, producer's accuracy, user's accuracy, and overall kappa coefficient were calculated for each site (Congalton and Green, 1999). Overall accuracy is the division of the total number of correct points by the total number of points. The producer's accuracy is the total number of correct points in a category divided by the number of points of that category as derived from the reference data (ground truthing). This accuracy indicates the probability that a reference point is correctly classified. The user's accuracy is the total number of correct points in a category divided by the total number of points of that category as derived from the classification data or map data. This accuracy indicates the probability that a point classified on the map actually represents that category on the ground. The overall kappa coefficient indicates how well the classification results agree with the reference data.

RESULTS AND DISCUSSION

Figure 1A shows the false color satellite image of site 1 on South Padre Island. The arrow points to the bright red image

Table 1. *An error matrix for the supervised classification generated from the classification data and ground data for the November 24, 2006, QuickBird satellite image of site 1 on South Padre Island, Texas.*

Classified Category	Actual Category: Mangrove	Wet Soil or Seagrass	Mixed Vegetation	Soil or Roads	Water	Total	User's Accuracy
Mangrove	23	0	1	0	0	24	95.80%
Wet soil or seagrass	0	58	0	0	0	58	100.00%
Mixed vegetation	5	2	15	4	2	28	53.60%
Soil or roads	0	1	0	29	0	30	96.70%
Water	0	0	0	0	10	10	100.00%
Total producer's accuracy	28	61	16	33	12	150	
	82.10%	95.10%	93.80%	87.90%	83.30%		

Overall accuracy = 90.0%. Overall kappa = 0.866.

response of black mangrove. Mixed vegetation has a light red to dull red color, wet soil or seagrass has a gray to grayish-red color, and soil or roads have a dark gray, white, or whitish-gray tone. Water has variable blue colors.

Figure 1B shows the supervised computer classification of the satellite image of site 1. Color codes for the various land-use types are: red = black mangrove, light green = mixed vegetation, dark green = wet soil or seagrass, white = soil or roads, and blue = water. Table 1 shows an error matrix comparing the classified data with the ground data for the 150 observations from the supervised classification of the image of site 1. The overall accuracy was 90%. The producer's accuracy for the individual categories ranged from 82.1% for black mangrove to 95.1% wet soil or seagrass, whereas the user's accuracy ranged from 53.6% for mixed vegetation to 100% for wet soil or seagrass and water. Black mangrove had a user's accuracy of 95.8%. Thomlinson, Bolstad, and Cohen (1999) set a target of an overall accuracy of 85% with no class less than 70%. Based on these guidelines, the overall accuracy was very good, as was both the producer's and user's accuracies for black mangrove. The errors in the producer's and user's accuracies for black mangrove identification were due to confusion with mixed vegetation. The poor user's accuracy of mixed vegetation identification was due to confusion with all the classes; however, the majority of the errors were caused by it being confused with black mangrove and soil or roads. Similar spectral characteristics among classes, as well as grading from one class to another, may have contributed to some of the errors among classes. Differences in error matrices may also be due to mapping error (Congalton and Green, 1999). The kappa estimate was 0.866, indicating the classification achieved an accuracy that is 86.6% better than would be expected from the random assignment of pixels to classes.

The error matrix comparing the classified data with the ground data for the 150 observations from the unsupervised classification of the site 1 image is shown in Table 2 (computer classification map not shown). The producer's accuracy for individual categories ranged from 50% for mixed vegetation to 100% for black mangrove. The user's accuracy for the individual categories ranged from 60.9% for black mangrove to 97.3% for soil or roads. The low user's accuracy of black mangrove identification was primarily due to confusion with mixed vegetation and wet soil or seagrass, while the poor producer's accuracy of mixed vegetation was mainly due to it being confused with black mangrove. The kappa estimate for the unsupervised classification was 0.731.

Tables 3 and 4 show the error matrices by comparison of the classified data with the ground data for the 150 observations from the supervised and unsupervised classifications, respectively, of the satellite image of site 2 (satellite image and computer classification maps not shown). The supervised classification had an overall accuracy of 90.7% (Table 3). Black mangrove had a producer's accuracy of 91.7% and a user's accuracy of 100%. The overall accuracy of the unsupervised classification was 85.3%; black mangrove had a producer's accuracy of 100% and a user's accuracy of 85.7% (Table 4). The producer's and user's accuracies of black mangrove

Table 2. *An error matrix for the unsupervised classification generated from the classification data and ground data for the November 24, 2006, QuickBird satellite image of site 1 on South Padre Island, Texas.*

Classified Category	Actual Category: Mangrove	Wet Soil or Seagrass	Mixed Vegetation	Soil or Roads	Water	Total	User's Accuracy
Mangrove	28	8	7	2	1	46	60.90%
Wet soil or seagrass	0	49	0	5	0	54	90.70%
Mixed vegetation	0	0	8	1	0	9	88.90%
Soil or roads	0	1	1	24	0	26	97.30%
Water	0	3	0	1	11	15	73.30%
Total producer's accuracy	28	61	16	33	12	150	
	100.00%	80.30%	50.00%	72.70%	91.70%		

Overall accuracy = 80.0%. Overall kappa = 0.731.

Table 3. *An error matrix for the supervised classification generated from the classification data and ground data for the November 24, 2006, QuickBird satellite image of site 2 at South Bay near South Padre Island, Texas.*

Classified Category	Actual Category					Total	User's Accuracy
	Mangrove	Soil	Mixed Vegetation	Seagrass	Water		
Mangrove	11	0	0	0	0	11	100.00%
Soil	0	76	2	0	0	78	97.40%
Mixed vegetation	1	0	13	1	2	17	76.50%
Seagrass	0	1	2	20	5	28	71.40%
Water	0	0	0	0	16	16	100.00%
Total producer's accuracy	12	77	17	21	23	150	
	91.70%	98.70%	76.50%	95.20%	69.60%		

Overall accuracy = 90.7%. Overall kappa = 0.861.

in both the supervised and unsupervised classifications were very good to excellent. The poor producer's accuracy of mixed vegetation identification in the unsupervised classification was due to confusion with soil and black mangrove. The kappa estimates for the supervised and unsupervised classifications were 0.861 and 0.776, respectively.

CONCLUSIONS

Our results indicate that QuickBird false color satellite imagery combined with computer image analysis can be used for distinguishing and mapping black mangrove along the south Texas Gulf Coast. The accuracy assessment results for black mangrove obtained from the supervised and unsupervised maps of the imagery were very good to excellent with the exception of the 60.9% user's accuracy of black mangrove from the unsupervised classification of the site 1 image. Accuracy assessment data from this study are better than that reported by Wang *et al.* (2004), who obtained user's and producer's accuracies for black mangrove ranging from 47% to 71% for IKONOS and QuickBird satellite imagery. Our results are comparable with those obtained by Everitt *et al.* (1999, 2007) for aerial photography, digital imagery, and videography; they reported user's and producer's accuracies for black mangrove ranging from 72% to 100%. They are also in close agreement to those reported by Yang *et al.* (2008) for airborne AISA + hyperspectral imagery; they reported user's and producer's accuracies for black mangrove ranging from 91% to 94%. The capability to remotely distinguish and map black mangrove populations with high resolution satellite imagery and image analysis techniques should be useful to coastal resource managers interested in population monitoring over large and inaccessible areas.

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Table 4. *An error matrix for the unsupervised classification generated from the classification data and ground data for the November 24, 2006, QuickBird satellite image of site 2 at South Bay near South Padre Island, Texas.*

Classified Category	Actual Category					Total	User's Accuracy
	Mangrove	Soil	Mixed Vegetation	Seagrass	Water		
Mangrove	12	0	2	0	0	14	85.70%
Soil	0	77	8	0	0	85	90.60%
Mixed vegetation	0	0	7	1	2	10	70.00%
Seagrass	0	0	0	19	8	27	70.40%
Water	0	0	0	1	13	14	92.90%
Total producer's accuracy	12	77	17	21	23	150	
	100.00%	100.00%	41.20%	90.50%	56.50%		

Overall accuracy = 85.3%. Overall kappa = 0.776.

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